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Fire Resistance Detection of Flammable Materials Based on Electronic Nose Technology

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The electronic nose system can identify and detect the toxic gases released by flammable materials during combustion. This paper studies the application of the e-nose technology in the early fire detection of flammable materials. Based on the brief introduction of the e-nose system and the associated pattern recognition technology, this paper builds a high-throughput flammable material fire simulation platform, and then, with the PVC material of the wires and cables in the electrical equipment which are prone to fire as an example, it detects the volatile substances within the safe operating temperature range (100-180°C) and at the warning temperature point (200°C) during the combustion process. In order to verify the anti-interference ability of the platform, this paper selects liquor and cigarette as interferences, which are also subject to detection in the experiment. It uses discriminant function analysis (DFA) and the BP neural network method to perform statistical analysis of the collected data and the results show that both methods have good discriminant effects. At the same time, it also optimizes the sensor array by the load analysis method. Through comparison and analysis, it is found that the eight-sensor array has a better discriminant effect. The research results show that the electronic nose technology can realize the early detection of flammable materials.

1. Introduction

Flammable materials is a general term for flammable solids, flammable gases and flammable liquids (Arnold et al., 2002). Out-of-control combustion of flammable materials will cause fires, one of the most frequent and devastating disasters that threaten public safety (Ferreiro-González et al., 2016). With the rapid economic development in China, various new technologies, equipment and technologies are being widely used. It can be said that flammable materials are everywhere in people's life. These flammable materials are potential causes of fires, so it is very necessary for people to understand the fire resistances of these flammable materials in order to prevent fires and achieve early fire detection and prediction.

The electronic nose technology (Falatová et al., 2018) is a new artificial intelligence technology developed and designed based on human's olfactory system to analyze and detect various odors within a short period of time. Due to its fast response and reliable discrimination, this technology has been widely applied in food and environmental testing, etc. Electronic nose devices were commercialized as early as 1995. At present, various related technologies have gradually matured, forming a good market scale (Milke and Mcavoy, 1995). Unlike in foreign countries, the researches on the electronic nose technology started quite late in China, and most of them are application-oriented. Despite certain results achieved in food quality assessment, the technology is in general not mature enough (Sun et al., 2012).

Flammable materials release a variety of toxic gases during combustion, and the electronic nose system can identify and detect these toxic gases (Belva et al., 2006; Razavi and Mohammadi, 2017). Therefore, this paper takes the e-nose technology as the detection tool and designs a high-throughput flammable material fire simulation platform, and then, with the PVC material of the wires and cables in the electrical equipment which are prone to fire as an example, it tests and analyzes the safe operating temperature and warning temperature of this material using the discriminant function analysis and the BP neural network method, with liquor and cigarette as interferences. The results show that both methods have good discriminant effects. At the same

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time, this paper also optimizes the sensor array by the load analysis method. Through comparison and analysis, it is found that the eight-sensor array has the best discriminant effect.

2. Related theories

Overview of the electronic nose system

The electronic nose system is an intelligent instrument that simulates the ability of human's olfactory system to recognize and perceive odor. It is composed of sensor array, signal preprocessing and pattern recognition (Çelik and Demirel, 2009). Figure 1 shows the working principle of the electronic nose, which can be described as a process where the sensor array converts odor information into electrical signals, which are then converted by the pre-processing module into digital signals that can be recognized by the computer and classified through a pattern recognition system (Ko et al., 2009).

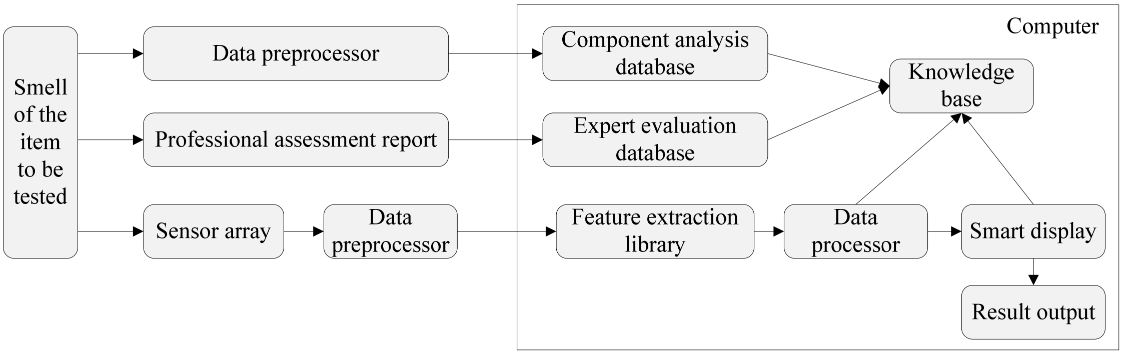

Figure 1: Working principle diagram of the electronic nose system

Pattern recognition technology

As the core of the electronic nose system, the pattern recognition technology plays a vital role in the detection speed and results of the electronic nose. Figure 2 shows the main components of the pattern recognition system (Gottuk et al., 2002). Based on whether the categories of the experimental samples are known in advance, the pattern recognition technology can be divided into supervised and unsupervised classification methods (Giglio et al., 2003).

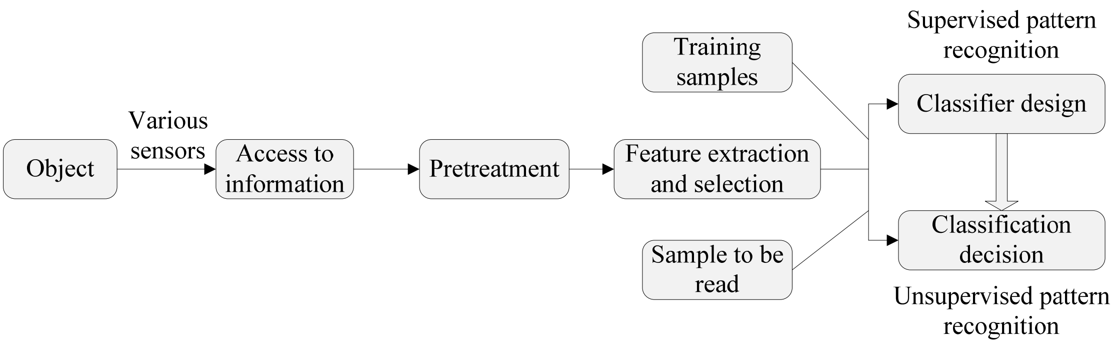

Figure 2: Main components of the pattern recognition system

Cluster analysis, network-based analysis and linear discrimination are the pattern recognition methods commonly used by electronic noses. Discriminant function analysis (DFA) (Koo, 1997) is a commonly used statistical-based linear analysis method, falling within the supervised pattern recognition category. It has such advantages as easy implementation and good classification effect. The The BP neural network (Cai et al., 2016) is a nonlinear processing model simulating the biological nervous system. The commonly used algorithm is the error back propagation algorithm, where the forward and back propagation processes alternate until the results converge (Tinianov and Surace, 2013).

3. Application of the electronic nose system in the fire resistance detection of flammable materials

3.1 Introduction of the experimental platform

Figure 3 shows the high-throughput flammable material (Ghasan et al., 2018) fire simulation platform designed for the application of the electronic nose in the fire resistance detection of flammable materials. This platform consists mainly of a computer, a test chamber, a sample cavity, a signal conditioning module and a flow and temperature control module (Kim et al., 2008).

In order to improve the test efficiency, this paper designs and fabricates a 36-array material chip, which contains 36 test electrodes and 4 grounded GND electrodes. The schematic diagram is shown in Figure 4.

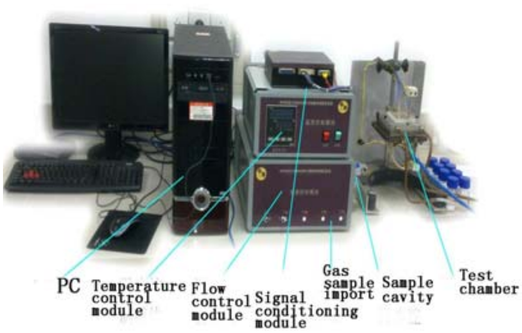

Figure 3: Picture of the high-throughput test platform

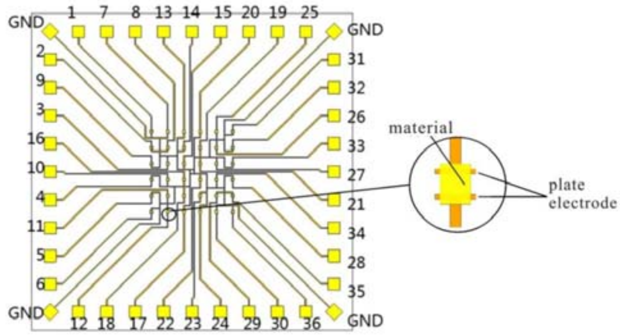

Figure 4: 36 Schematic diagram of the array material chip

3.2 Experimental content and process

The high-throughput flammable material fire (Zhang et al., 2018) simulation platform is used to test the wires and cables, which are made of PVC material. Some studies have shown that the PVC material starts to decompose at 200°C, so 200°C is set as the warning temperature point; that between 100-180°C, the gases released are mainly those emitted by the additive under heat, so this range is set as the safe working temperature point. In order to further verify the anti-interference ability of the electronic nose, cigarettes and liquors are used as interferences, and In_2O_3 prepared by the cotton-template method and WO_3 prepared by the sol-gel method are taken as the gas-sensitive materials. The gas-sensing responses of the cables at different temperatures are tested for 9 times, with a 1cm-long PVC insulated cable as the material each time. The interference gases are also tested for 9 times. This paper uses the electronic nose system to collect and analyze the data of the volatile gases after burning of wires and cables and optimizes the sensor array by the load analysis method, and discriminates the samples by the discriminant function analysis (DFA) and the BP neural network method.

3.3 Experimental results and analysis

3.3.1 Pattern recognition before array optimization

Since the experiment uses the 360-sensor array, the data obtained is huge. In order to facilitate classification calculation, it is necessary to obtain as few representative feature data as possible by reducing dimensions. The selection of eigen parameters is also one of the key factors determining the accuracy of pattern recognition. In this paper, the prediction model in this paper is established with sensitivity as the eigenvalue.

(1) DFA analysis

From Figure 5 - the sensitivity DFA analysis of the 36-sensor array, it can be seen that, the array can well distinguish the wire warning temperature, safe temperature, liquor and cigarettes. Among them, alcohol has a very different concentration due to its volatility, so the dispersion of liquor is large, while the dispersion of safe temperature is the smallest, indicating that the volatile components are similar between 100-180°C. The experimental results show that the DFA analysis method can retain the original data information more completely, with the total variance explained being 96.1%.

Chapter 2 (2) BP neural network analysis

Chapter 3 From the BP neural network sensitivity analysis of the 36-sensor array in Table 1, it can be seen that the BP neural network can distinguish the warning temperature, safe temperature, liquor and cigarettes, with a recognition rate of 100%.

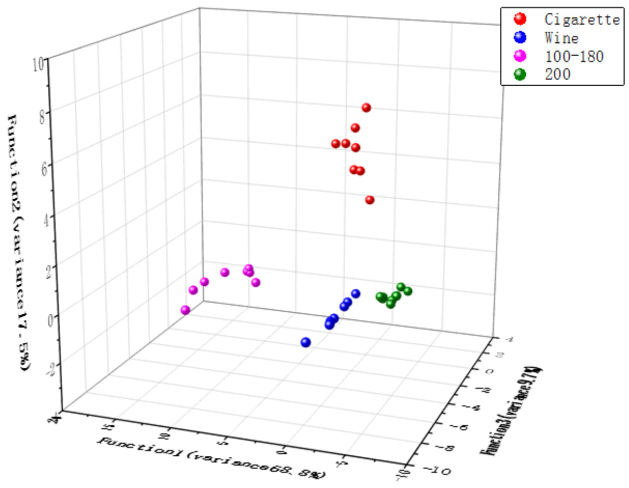

Figure 5: Sensitivity DFA analysis of the 36-sensor array

Table 1: Analysis of 36 Array Sensor Sensitivity BP Neural Network

Sample	Observed	C Classification				
		Cigarette	Liquor	100-180°C	200°C	Percent correct
Training	Cigarette	2	0	0	0	100%
	Liquor	0	6	0	0	100%
	100-180°C	0	0	10	0	85%
	200°C	0	0	0	7	100%
	Overall percent	5.2%	14.2%	12.84%	15.3%	82.5%
Holdout	Cigarette	5	0	0	0	100%
	Liquor	0	3	0	0	100%
	100-180°C	0	0	8	0	100%
	200°C	0	0	0	3	100%
	Overall percent	25.2%	0.6%	8.1%	0.6%	100%

3.3.2. Array optimization

In the electronic nose system, a plurality of sensors constitute a gas sensor array. When detecting gases, these sensors may provide much overlapping and redundant information, so in order to reduce the time of pattern recognition and improve the stability of the electronic nose system, this paper adopts the load analysis method to optimize the sensor array. Figure 6 shows the sensitivity analysis of the 36-sensor array, where the sensors are presented as S1-S36. The purpose of sensor array optimization is to eliminate the sensors that provide similar information. The closer the sensors are, the more similar information they will provide. Through experimental statistical analysis, eight sensors which can represent each category, namely S3, S7, S10, S13, S19, S23, S25 and S26, form a new sensor array.

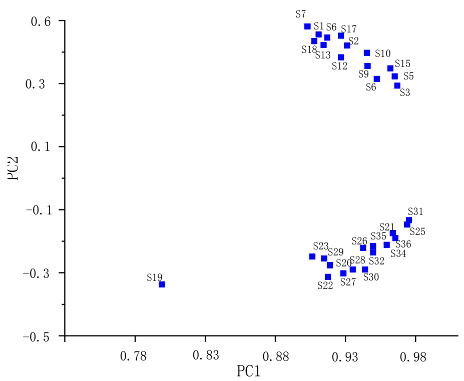

Figure 6: 36 Array sensor sensitivity load analysis diagram

3.3.3 Pattern recognition after array optimization

In order to verify whether the optimized eight-sensor array has a good anti-interference ability and realize the fire resistance detection of flammable materials, the optimized array is analyzed by linear discriminant DFA analysis and the BP neural network analysis.

(1) DFA analysis

The DFA analysis results of the optimized eight-sensor are shown in Figure 7. As can be seen, the eight-sensor array can distinguish the four categories more clearly than the one before optimization, and the spacing within each category is closer. The spacing between different categories is more obvious, showing that the discriminant effect is better. The total variance explained is up to 98.6%, indicating that it can comprehensively characterize the original information of the data.

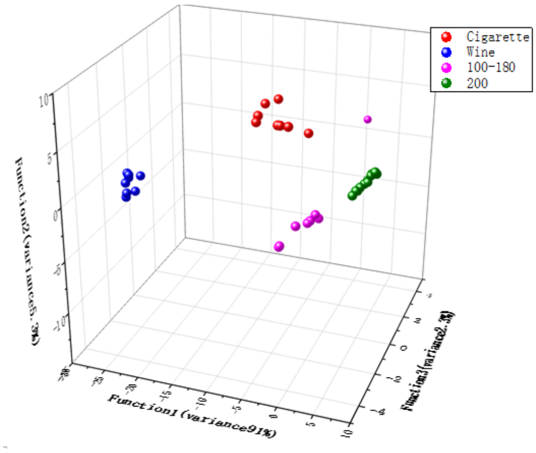

Figure 7: 8 array sensor sensitivity DFA analysis

(2) BP neural network analysis

The BP neural network analysis results of the optimized eight-sensor array are shown in Table 2 below. It can be seen that the optimized eight-sensor array can still well classify the test samples into four categories, with a recognition rate of 100%.

Table. 2 Analysis of 36 Array Sensor Sensitivity BP Neural Network

Sample	Observed	Classification				
		Cigarette	Liquor	100-180°C	200°C	Accuracy
Training	Cigarette	8	0	0	0	100%
	Liquor	0	7	0	0	100%
	100-180°C	0	0	9	0	88%
	200°C	0	0	0	6	100%
	Overall percent	13%	11.2%	31.6%	13.3%	97%
Holdout	Cigarette	2	0	0	0	100%
	Liquor	0	4	0	0	100%
	100-180°C	0	0	9	0	98%
	200°C	0	0	0	4	100%
	Overall percent	5.8%	21.1%	11.6%	13.4%	99.5%

4. Conclusions

Based on both domestic and foreign related literatures, this paper studies the application of the electronic nose technology in the fire resistance detection of flammable materials. The specific conclusions are as follows:

(1) To study the application of the electronic nose in the fire resistance detection of flammable materials, this paper designs a high-throughput flammable material fire simulation platform and also designs and fabricates a 36-sensor-array material chip to improve the platform testing efficiency.

(2) With the PVC material of wires and cables as the subject and liquor and cigarette as the interferences, this paper uses the designed platform to test the volatile gases during the combustion, and then distinguishes the

samples using the DFA analysis method and the BP neural network analysis method. The results show that the electronic nose system can achieve the fire resistance detection of flammable materials and have a good anti-interference ability.
(3) This paper optimizes the sensor array by the load analysis method. Through comparison and analysis, it is found that the eight-sensor array has a better discriminant effect.

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